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RESEARCH

Keeping Utah Moving

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16. Abstract

Snowplow trucks serve a crucial role in winter maintenance activities by removing, loading and disposing of snow. However, with the increase of service year, maintenance costs mount up and operational efficiency decreases due to more frequent repairs. As a result, managing the snowplow truck fleet effectively to minimize the total expense while guaranteeing high operational efficiency is necessary. In this study, we present a methodological framework using data-driven approaches to estimate the optimal life cycle for the Class 8 snowplow truck and its operational performance across the entire service span. Specifically, cost-benefit analysis is utilized to determine the optimal life cycle at macro-level, and a random forest (RF) model is implemented to analyze the fleet's micro-level performance. Leveraging the snowplot truck utilization data from 2000 to 2017 provided by the Utah Department of Transportation (UDOT), the analysis determined the optimal life cycle for class 8 snowplow trucks at 5 years. This result suggests a more frequent replacement cycle considering that most current snowplow trucks were replaced after 13 years of utilization. Meanwhile, the proposed RF model can be used to predict the performance at the micro-level, and it is able to identify the contributable factors to performance deterioration. The analysis indicates that annual working mileage, fuel consumption and service span are the main factors that lead to more maintenance and repairs of Class 8 snowplow trucks.

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UNIT CONVERSION FACTORS

SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. (Adapted from FHWA report template, Revised March 2003)

LIST OF ACRONYMS

AADT	Annual Average Daily Traffic
AATC	Annual Average Total Cost
ANN	Artificial Neural Network
AVL	Automatic Vehicle Location
CNN	Convolutional Neural Network
CTPP	Census Transportation Planning Products Program
CV	Cross Validation
DB	Declining Balance
DT	Decision Tree
ML	Machine Learning
OD	Origin and Destination
RF	Random Forest
UDOT	Utah Department of Transportation

EXECUTIVE SUMMARY

Snowplow trucks serve a crucial role in winter maintenance activities by removing, loading and disposing of snow. An effective performance monitoring and analysis process can assist transportation agencies in managing snowplow trucks and maintaining normal functioning of roadways. Yet these trucks' performance could deteriorate with age, incurring high maintenance costs and low efficiency. It is therefore necessary to determine the optimal utilization age for the replacement of these assets. To this end, we are presenting a methodological framework using a data-driven approach to estimate the optimal utilization age of snowplow trucks, taking into account both total costs and operational efficiency. Specifically, a cost-benefit analysis is conducted to determine the optimal life cycle for Class 8 snowplow trucks by leveraging purchase and resale data and maintenance costs through their service span.

Meanwhile, to further analyze the operational efficiency at micro-level and to identify the crucial factors that lead to performance deterioration, a machine learning (ML) approach, random forest (RF) model, is implemented to predict truck performance using endogenous and exogenous attributes and rank the importance of those attributes. This micro-analysis can assist transportation agencies to improve truck replacement strategy by identifying key factors affecting trucks' performance. Lastly, a sample application of the developed prediction model suggests the threshold of work intensity for preventing rapid deterioration of trucks' performance under various working environments.

For this project, the Utah Department of Transportation (UDOT) provides snowplow truck utilization data from 2000 to 2017. Exogenous features, such as weather and working environments, are collected as well for the purpose of analysis. According to the results of the cost-benefit analysis, the optimal life cycle for Class 8 snowplow trucks functioning in the State of Utah is 5 years. This analysis suggests a more frequent replacement cycle for snowplow trucks than what is currently implemented. Further, the annual working mileage, fuel consumption and service year are identified as the three most important factors associated with truck performance deterioration. The results provide additional guidance on the procurement, maintenance and replacement prioritization for Class 8 snowplow trucks.

1.0 INTRODUCTION

1.1 Problem Statement

Winter maintenance operation is essential to public mobility and safety, especially for areas suffering long periods of snow and storms (Kwon and Gu, 2017). In the United States, it is estimated that on average, annual winter road maintenance cost over $2.3 billion across the country in 2016 (FHWA, 2016). Winter maintenance operations involve applying de-icing chemicals, snow plowing, loading snow onto equipment and hauling the snow to disposal sites (Perrier et al., 2006). To fulfill these activities, snowplow trucks are paramount during the winter season, and an effective performance monitoring and analysis process would be beneficial to the program (Adams et al., 2003). On one hand, satisfying performance of snowplow trucks ensures efficient snow plowing, maintains normal functioning of the road network, and avoids any potential traffic accidents due to equipment malfunction. On the other hand, as the equipment ages, it becomes increasingly costly to maintain the trucks due to the expensive repair costs and rapid deterioration.

Currently, the Utah Department of Transportation (UDOT) manages hundreds of Class 8 snowplow trucks for winter maintenance activities including removing, loading, and disposing of snow. Generally, those snowplow trucks are sold once they are incapable of performing snowplow activities. Figure 1 shows the resale records of Class 8 snowplow trucks from 2000 to 2017. Notice that most trucks have a life span of over 13 years, and their life cycles are mostly concentrated between 15 to 19 years (highlighted in red in Figure 1). Yet with a longer service span, truck performance is deteriorating, causing lower operational efficiency and higher maintenance costs. For instance, a portion of Class 8 snowplow trucks are equipped with “nested C-channel” frame rails. This type of frame rail can accelerate corrosion due to entrapped salts used for de-icing. Meanwhile, repairs to frame rail cracks can be very expensive and are only temporary. The maintenance costs thus would accumulate as trucks age, making them less reliable in servicing roads. As a result, a reliable method to accurately estimate the optimal life cycle to minimize the overall costs for snowplow trucks is desirable.

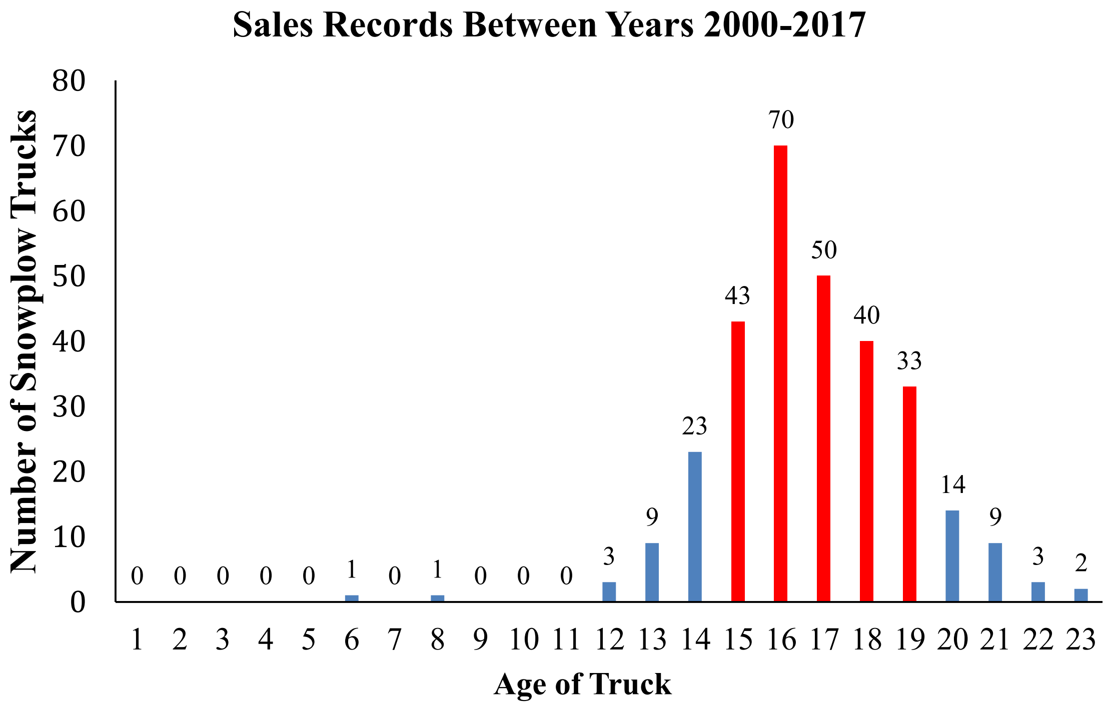


Figure 1 Resale records of Class 8 snowplow trucks from 2000 to 2017.

Meanwhile, other than only calculating the optimal life cycle, predicting truck performance and identifying crucial factors that lead to performance depreciation are paramount as well. First of all, a number of trucks may still maintain decent performance at "optimal" replacement year determined by the model. As a result, replacing all trucks completely could be a significant waste of resources. Additionally, a better understanding of the performance can assist agencies in refining their replacement strategy and systematically determine the service continuity/termination at the micro-level. This would enable an efficient maintenance program that takes advantage of variations in truck performance. As a result, if truck performance can be monitored and predicted with high resolution and high accuracy, they can be replaced in time and help cut down maintenance expenses.

1.2 Objectives

This research project focuses on analyzing the life cycle and operational efficiency of Class 8 snowplow trucks in the State of Utah. Currently, UDOT is managing hundreds of Class 8 snowplow trucks. According to resale records, most of them were replaced after servicing over

13 years. However, more frequent repairs can occur, accompanied with higher maintenance costs, as truck performance deteriorates with service age. As a result, it is necessary to conduct data-driven analysis to evaluate the total cost and find the best replacement cycle that minimizes the overall costs of the truck fleet while guaranteeing satisfactory performance during their service span.

The first objective of this project is to develop a method to determine the optimal replacement year for the Class 8 snowplow truck fleet managed by UDOT. To achieve this, purchase and resales information, maintenance records, and working mileage records are used in this study. Specifically, purchase and resales records are used to estimate the cumulative depreciation cost with the increase of trucks' service span. Then the maintenance costs are utilized to reflect the maintenance expense with inflation rate at different service years. Lastly, a cost-benefit curve is constructed to decide the optimal life cycle, which minimizes the overall costs for the snowplow truck fleet.

Another objective of this project is to propose a machine learning (ML) technique, Random Forest (RF) model, that is capable of predicting truck performance with performance-related endogenous and exogenous variables. Although the cost-benefit analysis helps transportation agencies identify the optimal replacement cycle for snowplow trucks, this macro-level analysis fails to evaluate the operational efficiency for a single truck, and cannot capture key factors contributing to performance deterioration. In fact, a better understanding of truck performance can find existing trucks that may still maintain adequate performance at "optimal" replacement years determined by the model, thus avoiding wasting resources. Moreover, it can help agencies in complementing their replacement strategy and systematically determining the service continuity/termination at the micro-level. This enables a more efficient maintenance program: one that takes advantage of variations in truck performance.

1.3 Scope

This research breaks down into two parts: Estimating the optimal life cycle for Class 8 snowplow trucks, and predicting the operational performance of trucks with different work intensities and in different working environments.

Tasks in optimal life-cycle analysis include:

- Aggregate the maintenance costs data with consideration of inflation rate;
- Build depreciation cost curve using trucks' purchase and resales data; and
- Perform a cost-benefit analysis to construct the overall costs curve for Class 8 snowplow trucks with different service ages, and pinpoint the optimal replacement year.

Tasks in truck performance prediction at micro-level include:

- Implement RF to predict truck performance with snowplow trucks' endogenous and exogenous features;
- Identify the contributable factors leading to performance deterioration; and
- Suggest the threshold of work intensity for preventing rapid deterioration with a sample application.

To conduct the aforementioned tasks requires the support of a mass amount of historical data from multiple resources and jurisdictions. UDOT provides thorough utilization information of Class 8 snowplow trucks from 2000 to 2017 with 831 trucks in total, including working mileage data, maintenance costs records, and resales records. All snowplow trucks are distributed in the four regions statewide, namely the Salt Lake City region, Ogden region, Orem region, and Richfield region. Meanwhile, exogenous features, including terrain and weather information, are collected from other sources to further analyze the potential factors that cause the decrease in operational efficiency.

1.4 Outline of Report

The rest of the report is structured as follows. Chapter 2 summarizes literature on the cost-benefit analysis for the truck fleet and performance-prediction analysis using RF. Chapter 3 illustrates the detailed formulation of the cost-benefit method and RF model. Chapter 4 describes the data sources used for this study, and Chapter 5 presents the results and findings. Lastly, Chapter 6 concludes the study and outlines recommendations for future research.

2.0 LITERATURE REVIEW

2.1 Overview

Cost-benefit analysis enables finding the optimal replacement cycle for a fleet of assets while RF can identify crucial factors causing performance depreciation of the fleet. This chapter presents the summary of previous studies on snowplow-truck fleet life-cycle analysis and performance prediction using RF.

2.2 Parallel Snowplow-Truck Fleet Life-Cyle Analysis

Past studies have witnessed the importance of snowplow trucks as the primary tool for public agencies to deliver their winter maintenance program. An effective snowplow program can reduce congestion, avoid hazards to pedestrian safety, and mitigate economic losses (Changnon and Changnon, 2007; Hanbali and Kuemmel, 1993; Li and Fernie, 2010). Naturally, the performance of snowplow trucks is of critical importance to the regions where winter storms and snowfalls are frequently encountered. Thus, developing an effective performance monitoring and analysis process would be beneficial to the program. For example, a good performance from snowplow trucks ensures efficient plowing, maintains normal functioning of the road network, and avoids potential traffic accidents due to equipment malfunction. Conversely, as the equipment ages, it becomes increasingly expensive to maintain the trucks due to repair costs and rapid deterioration. If not replaced at an earlier age, a truck can continue to bring up the lifecycle cost. For instance, frequent usage of snowplow trucks can result in cracked frame issues due to erosion from snow. A cracked frame increases the risks to operators and pedestrians and the replacement for the entire truck frame is quite costly, at approximately $45,000. Given these considerations, it might be more cost effective to replace snowplow trucks with a properly selected cycle (Fan et al., 2011). To solve this problem, a method that can determine the life cycle with minimal overall costs for the snowplow truck fleet while guaranteeing needs and operational efficiency for road service is required.

Previous studies related to snowplow-truck fleet life-cycle assessment attempted to address this issue via cost-benefit analysis. With that approach, the total cost curve across the assumed service span is constructed, which consists of equipment purchase, maintenance, and depreciation costs. The goal is usually to determine an optimal life cycle that minimizes overall costs while guaranteeing operational efficiency across fleet service spans (Litman, 1998). For instance, Iowa DOT proposes a decision support system (DSS) based on cost-benefit method to optimize the equipment life cycle (Scheibe et al., 2017). Specifically, two types of snowplow trucks are analyzed in this study, the single-axle A07 and double-axle A12 snowplow trucks, which both have a replacement cycle of 15 years. To obtain the optimal life cycles, historical data over the past 9 years including purchase price and date, maintenance cost, and actual resale values are extracted. Additionally, they adjusted the maintenance event costs with an inflation rate of 4.23% for comparative analysis. By building total cost curves with cost-benefit method, the result suggests an optimal life cycle of 8 years for A07 and 6 years for A12. It is estimated that Iowa DOT could save approximately $8.2 million every year by shortening the current lifecycles to the recommended ones. In fact, the calculated optimal life cycle can vary greatly among different types of snowplow trucks. Wyrick and Erquicia (2008) use a similar approach to analyze the optimal life cycles for seven different types of snowplows in the state of Minnesota and conduct sensitivity analysis for purchase price, interest rate, depreciation value, and maintenance cost. The results indicate that the optimal replacement cycles range from 5 to 13 years based on different types of trucks. This conclusion suggests the necessity of analyzing the optimal life cycle for Class 8 snowplow trucks based on their own circumstances in the State of Utah.

2.3 RF Model and Performance Prediction

RF is one of the ML methods. ML approaches analyze data first and then automate the building process of analytical models. These models can help identify potential patterns from the data and make predictions with minimal human intervention (Alpaydin, 2009). Currently, researchers use ML models for performance prediction in many fields, including finance, healthcare, engineering, marketing and manufacturing, among others (Langley and Simon, 1995). For example, Ghobadian et al. (2009) use an artificial neural network (ANN) to predict diesel engine performance with regards to fuel consumption and exhaust emissions. Ma et al. (2017) apply convolutional neural network (CNN) to predict traffic speed to analyze the performance of a large-scale network. Although both ANN and CNN generate high levels of predictive accuracy, they are not capable of interpreting the importance of various inputs to the results. RF is a classic tree-based ensemble model proposed by Breiman (2001). It combines multiple base models and derives the final result via weighted or unweighted voting or averaging (Dietterich, 2000). The main idea behind the ensemble model is that a series of base models can generate a more stable prediction and have stronger generalization ability than a single base model. In RF, the base models are decision trees (DTs). Apart from its stable structure, another highlight of RF is that it enables interpretation of feature importance by ranking those variables based on its interior tree structure.

In fact, RF can be used for maintenance performance prediction for assets. A good illustration of this method is Bukhsh et al. (2019), where the authors use tree-based classification models, including DT, RF, and gradient-boosting decision tree, to predict the maintenance of railway switches. The results indicate that RF achieves the highest accuracy (0.70) for classifying the maintenance type among all models. In this case, accuracy is a measure of correct predictions using the model compared to the total data points. Meanwhile, Bukhsh et al. also find that functional location, service years and detected problems are the most important features in affecting the status of switches. This interpretability can facilitate the decision-making process for infrastructure managers and help prioritize future data collection efforts.

2.4 Summary

This chapter first summarized previous literature of truck fleet life-cycle analysis via cost-benefit method. Following that, a popular machine learning algorithm RF is introduced, which is often used for performance prediction problems at the micro-level. In the following chapters, we describe the mathematical formulation of cost-benefit method and RF, and subsequently demonstrate how these methods can be applied to obtain the optimal life cycle and evaluate the operational performance of a Class 8 snowplow truck fleet.

3.0 RESEARCH METHODS

3.1 Overview

This chapter describes cost-benefit method and RF model, respectively. The cost-benefit method utilizes maintenance information and estimates the depreciation trend of the snowplow truck fleet to pinpoint the optimal life cycle. RF is capable of predicting truck performance by learning features related to trucks' work intensity (e.g. working mileage) and working environments (e.g. traffic volumes of the roads they serve).

3.2 Cost-Benefit Method for Truck Fleet Analysis

Cost-benefit analysis takes overall costs of the assets into consideration by constructing economics curves to identify the optimal life cycle. For a snowplow truck fleet, two types of costs are mainly considered - the maintenance cost and depreciation cost. This section introduces the procedure of building the average total-costs curve for a truck fleet across different service spans.

3.2.1 Maintenance Costs Calculation

Maintenance costs refer to the expenses of any required repairs as well as the costs of preventive maintenance during their service span. The maintenance costs for Class 8 snowplows are generally originated from facility replacement and labor costs with related technicians. Additionally, it is important to consider the inflation rate to adjust the costs. This is because maintenance records span a long period of time up to 17 years. In order to construct the maintenance cost curve, the following steps are conducted:

- Aggregate the maintenance records by service years for each snowplow truck, and sum up the total maintenance costs for all trucks at each service year;
- Adjust the total annual maintenance costs with the inflation rate accordingly based on different service years; and
- Divide the number of trucks in service at each service year with the corresponding adjusted annual total maintenance costs.

As a result, we can obtain the adjusted average maintenance costs at different service years, which can be further used for cost-benefit analysis. It is noted that the concept of service year is different from the concept of actual year. Service year refers to the time period from the time point that a truck started to service the roads. Two trucks with the same service year can be operating at different actual years. For instance, two snowplow trucks started their service at 2000 and 2001 respectively (actual year), and both functioned for one year. In this case, they have the same service year of one, but the service year happens at different actual years.

3.2.2 Depreciation Cost Estimation and Calculation

Depreciation refers to the decrease in asset value in response to time. For Class 8 snowplow trucks, their values start to decrease as they start to service the road. With the increase of service span, the depreciation cost for each service year is accumulating. In other words, the assets' surplus value is decreasing with longer service span. The relationship between the cumulative depreciation cost and surplus value can be expressed as follows:

$$p_{purchase} = sv_n + c\_dep_n \quad (1)$$

where $p_{purchase}$ stands for the original purchase price, sv_n is the surplus value at the nth service year, and c_dep_n is the cumulative depreciation costs at the nth service year.

Yet in most cases, surplus value is not available. To estimate the cumulative depreciation cost across different service years, the declining balance (DB) method is used to predict the annual depreciation value of snowplow trucks first, and then cumulative depreciation cost can be derived. DB method is an accelerated depreciation method, in which the depreciation expense is the highest in the initial year and declines over service time (Mayer, 1947). The formulation for depreciation under the DB method is expressed as follows:

$$p = 1 - \sqrt[n]{\frac{s}{c}} \quad (2)$$

where p is the percentage of annual depreciation; n is the number of years of useful life; s is the surplus value at the n^{th} year; and c is the original purchase cost. Once the percentage of annual depreciation p is derived, the annual depreciation cost at a given service year (k) can be calculated based on the method as:

$$dep_k = c * (1 - p)^k \tag{3}$$

Finally, the cumulative depreciation costs from the start of service to the k^{th} service year can be derived as:

$$c\_dep_k = \sum_{i=1}^{k} dep_i \tag{4}$$

In order to obtain the percentage of depreciation p in Equation 2, we use the average resale value of trucks at a specific service year to represent the surplus value in this analysis. The detailed calculation will be presented in Chapter 5.2.

3.2.3 Cost-Benefit Method

Cost-benefit analysis enables the determination of optimal life cycle by observing the economic curve across different truck fleets' service spans. Once the maintenance cost curve and cumulative depreciation cost curve are constructed, the annual average total cost (AATC) per truck per mile given a specific life cycle *N* for Class 8 snowplow trucks can be formulated as follows:

$$AATC_N = \sum_{i=1}^{N} \left(\frac{Maintenance_i}{T_i} + Dep_i\right) / (N * Mi_N) \tag{5}$$

where $Maintenance_i$ is the overall adjusted maintenance costs at the i^{th} service year; T_i is the total number of trucks in service at the i^{th} service year, Mi_N is the sum of mileage records from the initial service year to the end of the life cycle. Finally, the cost-benefit curve can be plotted by calculating AATC with different life cycles *N*. The life cycle with the lowest cost in the curve is identified as the optimal life cycle (or replacement cycle) for Class 8 snowplow trucks.

3.3 Framework of RF Model

RF is a tree ensemble model, which consists of a number of base models. In this subsection, we first introduce the mechanism of its base model, the decision tree. Then, we detail the formulation of RF, the process of performance prediction, and its ability to identify the important factors influencing its performance.

3.3.1 DT Model

DT is a popular supervised learning algorithm because it is computationally efficient. The tree-shaped model can split the data by different attributes for classification or regression purposes. Generally, a decision tree consists of a root node, several interior nodes and leaf nodes. One feeds training data into the root node and then splits these data into different interior nodes, based on data attributes. The node that helps split the dataset is called the *father node*, and the nodes after branching are called *children nodes*. If the samples in one node belong to the same class, this node terminates branching and becomes a leaf node. The tree grows recursively until all samples are assigned to leaf nodes. There are a range of additional models, built upon the basic structure of DT, that modify rules associated with data splits, branching and subtree pruning. The most popular DT models include ID3 (Quinlan, 1986), C4.5 (Quinlan, 2014) and classification and regression tree (CART) (Breiman, 1984) models. We detail the pseudocode for a simplified DT model in Figure 2.

```
define an empty decision tree T and feed the data into the root node
while True{
    select one attribute that maximizes the information gain, and
    split the data from the father node into children nodes
    if the samples are pure in the children node:
        terminate branching and form a leaf node
        if all samples are assigned to the leaf nodes:
            break
    else if all attributes are used out for splitting:
        break}
Prune the decision tree T
Return T
```

Figure 2 Pseudocode for a simplified decision tree model.

In this pseudocode, information gain is an index to measure the classification ability given by one attribute. The larger the information gain, the stronger the classification ability. For each split, it chooses the attribute that can maximize the information gain. For instance, in CART (a binary decision tree), information gain by feature *k* is:

$$Information\ Gain_{(k)} = Gini_{father} - \left(\frac{|S_{left}|}{|S|} * Gini_{children(left)} + \frac{|S_{right}|}{|S|} * Gini_{children(right)}\right) \tag{6}$$

where $|S|$, $|S_{left}|$ and $|S_{right}|$ represent the number of samples in father node, the number of samples in the left children node, and the number of samples in the right children node, separately. $Gini$ is the index to describe the impurity of the node:

$$Gini = 1 - \sum_{i=1}^{N} {P_i}^2 \qquad (7)$$

where P_i is the probability of the ith event happening in the node. In the classification decision tree, event corresponds to the fraction of a class in one node.

3.3.2 RF Model

However, one disadvantage of DT is the propensity to overfit the model, even when actively pruning. Moreover, the model is highly sensitive to dataset, which means that the structure of the tree may deviate significantly even when a small portion of the training data is changed. To supplement the performance of DT, one can use several tree ensemble models, including RF.

RF uses CART (Breiman, 1984) as its base model. The basic idea of RF is that it generates a number of trees and combines them by weighted or unweighted averaging or voting the results from each tree. The superiority of RF is attributable to bootstrap aggregating and random feature selection techniques (Breiman, 2001). The bootstrap aggregating method enables each DT to train with a subset of the data with replacement. Meanwhile, feature selection strategy allows a limited number of randomly chosen features from each tree for training. By applying these two techniques, RF is able to generate a number of different DTs and merge them into a robust tree ensemble. RF outperforms single DT by mitigating overfitting and sensitivity of the dataset effectively. Apart from that, one can generate trees in RF via parallel computing to reduce computational complexity. Figure 3 details the pseudocode for constructing a simplified RF model.

```
define a RF with M empty trees and import the dataset N
for i=Tree(1),…,Tree(M) do {
   use bootstrap aggregating method to draw samples from dataset N;
   randomly choose T' variables from T variables (T'≤T);
   train the samples with the CART model using T' variables;
 }
combine M trees together
return f(Tree(1)+…+Tree(M))
```

Figure 3 Pseudocode for a simplified RF model.

In Figure 3, M is the total number of trees; N is the size of training samples, and T is the number of input variables. When one uses RF for regression tasks:

$$f\left(Tree_{(1)} + \cdots + Tree_{(M)}\right) = \frac{1}{M}\sum_{m=1}^{M} Tree_{(m)} \tag{8}$$

Alternatively, when one uses RF for classification tasks:

$$f\left(Tree_{(1)} + \cdots + Tree_{(M)}\right) = argmax_{c\in y}\left|\left\{m|Tree_{(m)} = c\right\}\right| \tag{9}$$

where y is the total number of classes in the classification task.

Besides the robust structure, another important trait of RF is its ability to interpret feature importance. In DT, every node split uses a single feature. One can compute the decrease of impurity (i.e., information gain in Equation 6) accordingly and rank features according to the average decrease in impurities across all trees in the forest. By identifying the important features in determining snowplow trucks' performance, transportation agencies can make informed decisions on truck replacement. For instance, if pavement conditions are the dominant force in affecting truck performance, trucks serving roads with poor pavement should operate less frequently and/or be replaced sooner.

3.4 Summary

In this chapter, mathematic formulations of cost-benefit method and RF are presented. Cost-benefit analysis focuses on overall truck fleet costs, while RF analyzes the truck performance at the micro-level. RF can complement the optimal life-cycle decision by providing a better understanding of critical factors leading to performance deterioration for transportation agencies. In the following chapter, we introduce the detailed datasets used in this study.

4.0 DATA COLLECTION

4.1 Overview

The proposed methods are applied to determine the optimal replacement cycle and examine the performance of Class 8 snowplow trucks operated and maintained by UDOT. The dataset contains the snowplow trucks' performance and utilization records for years 2000 through 2017. Additionally, working environment information from multiple sources is collected for analyzing truck performance. Since the life-cycle analysis and performance evaluation use different approaches and datasets, data sources for each method will be introduced in the following subsections, separately.

4.2 Dataset for Cost-Benefit Analysis

The AATC curve for cost-benefit method consists of the maintenance cost and depreciation cost. To derive AATCs with the variation of life cycles, a series of utilization information for Class 8 snowplow trucks is needed. Detailed descriptions of the datasets used are listed below:

- **Maintenance costs records**
  The maintenance costs for each snowplow truck are recorded monthly from 2000 to 2017. Maintenance can be classified as commercial repairs and non-commercial repairs, where commercial repairs denote restorations by professional technicians from third-party companies and non-commercial repairs are restorations by UDOT. The maintenance cost is aggregated by service year to obtain the optimal life cycle.
- **Number of trucks**
  The number of trucks serving at the same service year is not equivalent to the number of trucks serving at the same actual year. This information is required for calculating the annual average total cost per truck. The records indicate that there were 831 Class 8 snowplow trucks in total serving the roads from 2000 to 2017 in the State of Utah. The oldest snowplow truck started its service in 1979 and the latest one started in 2017. For the first service year, there are 473 trucks in total. However, the number of trucks decreases with the longer service span. At the 17^{th} service year, there are only 32 trucks with available service records.

- **Mileage records**

  The mileage records for each snowplow truck are documented monthly. We sum up the mileage data by each service year to calculate AATC per truck per mile. The provided data is determined to be of high quality with approximately 0.21% erroneous recording on mileage of extremely large values. Further filtering is conducted through interpolation to replace those outliers with averaged odometer records of previous and following months.

- **Original purchase data**

  The purchase data includes original purchase price and purchase date for each truck. There were 521 Class 8 snowplow trucks purchased during the years 2000 to 2017 in total. The purchase records are used for DB method and inflation-rate evaluation to adjust maintenance costs in different actual years.

- **Disposition information**

  The Class 8 snowplow trucks will be sold once they cannot function normally and serve the roads. Resale information contains resale price and date. The disposition data is utilized to estimate the percentage of annual depreciation for DB method. According to the dataset, there were 301 Class 8 snowplows sold with valid information from 2000 to 2017.

- **Label of working regions**

  The Class 8 snowplow trucks are assigned to different working regions in the State of Utah. Each truck is labeled with a specific working region. The four working regions include the Salt Lake City region, the Ogden region, the Orem region, and the Richfield region. Cost-benefit analysis can be performed based on different regions to explore the variation of optimal life cycles across geographical areas.

4.3 Dataset for Truck Performance Prediction

RF is one of the popular ML models utilizing performance-related variables to predict the entity's operational efficiency. For prediction purposes, information such as repair costs for each downtime, working mileage and fuel consumption per month, service year and load type for each truck is extracted. Endogenous variables such as working mileage and fuel consumption are further aggregated into annual average consumption across each truck's entire service span to implement the proposed method.

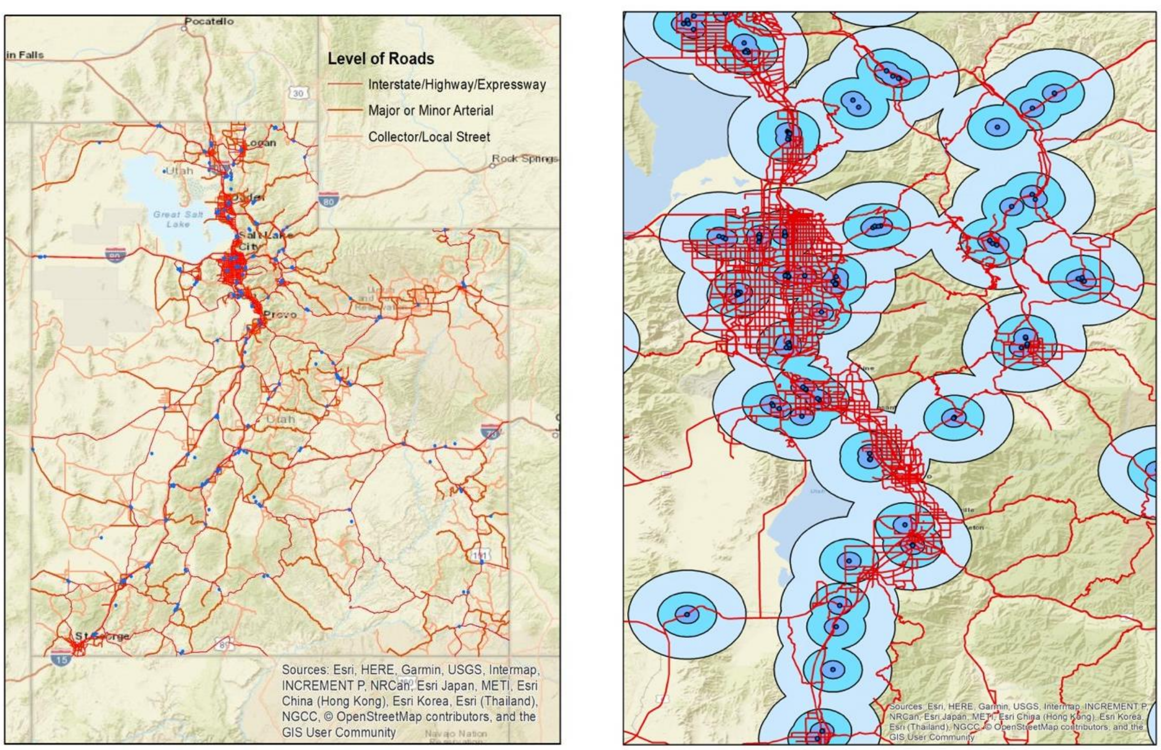
Other than the endogenous variables that could impact snowplow truck performance, we hypothesize that exogenous factors such as weather and terrain type could also potentially affect their operation. Additional data such as snow depth records from 2000 to 2017, functional classifications and annual average daily traffic (AADT) of roads in the state of Utah, and land-use data indicating whether the truck serves an urban or rural area are collected for the purpose of this study. Meanwhile, all snowplow trucks are equipped with Verizon Automatic Vehicle Location (AVL) technology. Verizon AVL is a fleet-tracking system which enables monitoring and managing the entire mobile equipment. This GPS fleet-tracking system records trucks' location and speed information every two minutes, which allows near real-time monitoring of the fleet. To delineate the territorial and/or land-use impact on snowplow truck performance, the origin and destination (OD) data of each active trip for every truck was retrieved between February 6 to March 31, 2018, when the trucks were performing major winter maintenance activities. An active trip refers to the daily trajectory of snowplowing activity for each truck. Table 1 lists detailed information of all variables collected.

Table 1 Detailed description of all variables.

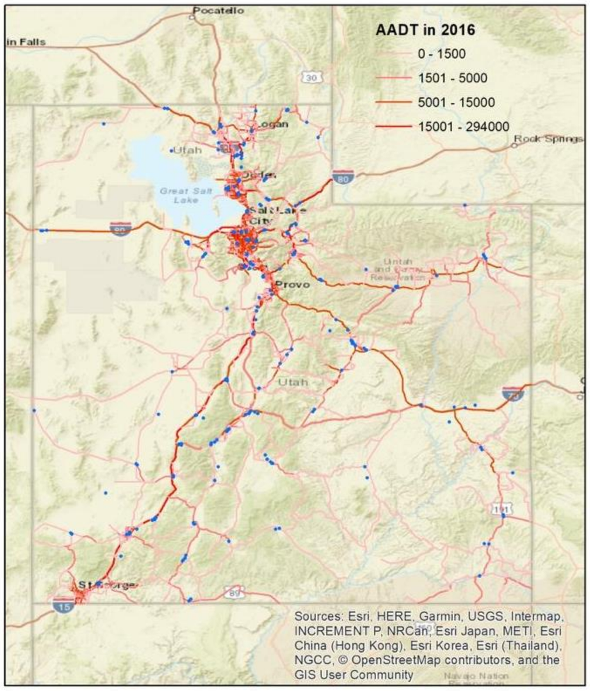
Variables	Denotation	Description	Unit	Resource
Year	service year	The service year is determined from the start year to 2017 if the truck is still in service, otherwise it is determined from the start year to the year that it is sold.	year	Utah DOT
Fuel	annual average fuel consumption	It records the annual average fuel consumption for each truck during its service span.	gallon/year	Utah DOT
Mi_winter	annual average mileage in winter season	The annual average for each truck in winter season during their service span. Winter season is defined from November to March (in the year to follow).	mile/year	Utah DOT
Mi_other	annual average mileage in other seasons	The annual average mileage for each truck in other seasons during their service span. This is to delineate other operational-similar activities that snowplow truck might take on outside the winter season (e.g. the fire truck).	mile/year	Utah DOT
Type	load type	The class 8 snowplow trucks are classified into three types, Type 104, Type 113 and Type 168 with numbers representing the capacity for snow.	NA	Utah DOT
Func	functional classification of the roads	The roads are categorized into seven levels, with 1 representing the highest level and 7 representing the lowest level based on the functional classification: 1: Interstate 2: Other freeway and expressway 3: Principal arterial 4: Minor arterial 5: Major collector 6: Minor collector 7: Local streets	NA	Utah DOT
Vol	AADT in 2016	The AADT in 2016 is used to reflect the volume of each road.	veh/day	Utah DOT
Snow	annual average snow depth during truck's service span	We average the snow depth for each truck during their service span to reflect the workload across different trucks.	ml	MesoWest
Area	service area type	The snowplowing activity region is distinguished by urban vs. rural regions.	NA	CTPP
Rank	rank of major repair times	The rank of major repair times is used to quantify the performance of snowplow trucks. It is categorized as follows: Rank 1: 0-4 times Rank 2: 5-8 times Rank 3: 9-12 times Rank 4: over 12 times	NA	Utah DOT

After acquiring exogenous features, data association is performed to link them with each truck. For example, a snowplow truck should only be linked with roads that are in close vicinity of its working region. To conduct truck and exogenous features association, we resort to the

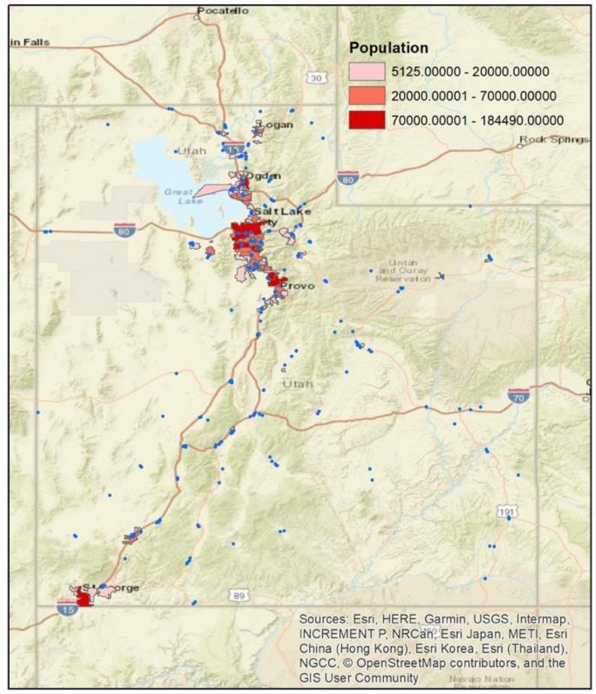
AVL OD data to estimate the centroid of snowplowing activity. As mentioned earlier, the OD data include the origin and destination points for daily active trips of trucks spanning February 6 to March 31, 2018. Note that most daily snowplowing activity is a round trip, where the origin and destination coordinates are quite close for each truck. We therefore average the coordinates of all origin and destination points for each snowplow truck to approximate the centroid of snowplowing activity. Once the centroid is determined, different ring buffers with varying radiuses (i.e. 2km, 5km, and 10km) are created to capture the roads that each truck serves, as shown in Figure 4 (a) and (b). Such attempts determined that for 95% of trucks, 2km are sufficient to capture the nearby roads that the trucks work on. The road functional classification is labelled from 1 to 7, with 1 representing the highest level of mobility and 7 representing the lowest level of mobility. The functional classification variable is further averaged out for the roads encompassed within the buffer to represent the road characteristics that the truck serves. The remaining 5% of trucks that fail to capture nearby roads are replaced with the average functional classification value of the 95% of trucks.



(a) (b)



(c)



(d)

Figure 4 The functional classification of the roads and the distribution of the centroids of snowplow activities (a); a portion of snowplow trucks with ring buffers (b); the 2016 AADT of all roads in the state of Utah (c); the distribution of urban area in the state of Utah (d).

We further extracted the 2016 AADT of roads that each truck serves using a similar approach as described above. The land-use types are roughly classified into rural vs. urban, with an urban area defined as a census tract that has a population of more than 5,000 people, and the place outside is regarded as a rural area (Hall et al., 2006). This land-use feature is determined by the census tract that the truck's centroid of activity falls into. Population data in the State of Utah from 2006 to 2010 is extracted from the Census Transportation Planning Products Program (CTPP), a State DOT-funded cooperative program (CTPP, 2019). The AADT and urban areas are displayed in Figure 4 (c) and (d). Lastly, snow depth of each year is retrieved from MesoWest, a program started at the University of Utah providing access to current and historically archived weather observations (MesoWest, 2019). Snow depth is averaged across the years of which every truck serves.

In this study, frequency of major repairs is used as the main indicator to classify the performance of all trucks. This is because satisfactory machine performance would result in good maintenance efficiency and less repair times (Swanson, 2001). Previous studies show that a single major repair caused by snowplowing activities (e.g. replacement of the axles) is around $2,500 on average (Cuelho and Kack, 2002). For simplicity, we define major repair in this study as any repair record that costs over $2,000. Based on the range of frequency of major repairs for all trucks, we categorized them into four ranks, with detailed classification shown in Table 1. Overall, Rank 1 represents trucks with good performance, while Rank 4 indicates poor performance.

Although there were a total of 831 trucks in service between years 2000 to 2017, a portion of the trucks (420) started their service prior to the year 2000. Due to data unavailability, those trucks are removed from the modeling effort. The OD data from AVL missed activity records of 21 trucks due to such causes as resales, temporary maintenances, etc. Eventually, 388 snowplow trucks with complete records are used for performance prediction.

4.4 Summary

In this section, the datasets for life cycle and truck performance analysis are described in detail. For cost-benefit analysis, utilization data, purchase, and resale information are leveraged to build AATC curve. For performance-prediction analysis, not only utilization information is used, exogenous variables quantifying trucks' working environments are collected as well. In the next chapter, we will present the implementation of the proposed methods.

5.0 CLASS 8 SNOWPLOW TRUCKS PERFORMANCE ASSESSMENT

5.1 Overview

In this chapter, cost-benefit analysis is implemented to obtain the optimal life cycle for Class 8 snowplow trucks utilizing the dataset described in Chapter 4. This analysis suggests the fundamental strategy for minimizing the overall costs for fleet management. Subsequently, RF is proposed to predict truck performance with both endogenous variables and exogenous variables related to snow-plowing activities. This analysis explores the important factors accelerating performance depreciation, which can help UDOT to complement the replacement strategy effectively for Class 8 snowplow trucks.

5.2 Cost-Benefit Method for Optimal Life-Cycle Analysis

5.2.1 Inflation Rate and Maintenance Cost

Inflation is a sustained increase in the general price level of goods and services in an economy over a period of time. According to the resale records in Figure 1, the average purchase price for one Class 8 snowplow truck is below \$100,000 in 2000, while the average purchase price reached approximately \$150,000 per truck in 2017. This change indicates the necessity of taking inflation into account when calculating the total costs throughout its entire life span. For maintenance cost records, trucks can be at the same service year but at different actual years. As a result, those maintenance costs needs to be multiplied by the inflation rate of the corresponding years. Iowa DOT’s study (Scheibe, 2017) used an annual inflation rate of 4.23%. To derive the fitted inflation rate in this study, we use the average purchase price in 2000 as the base, and predict the purchase price for the following years with various inflation rates (i.e. 4%, 5%, and 6%) up to 2017. The results are presented in Figure 5. In this figure, it can be observed that if setting 4% as the inflation rate, the purchase prices are underestimated for most of the years; while a 6% inflation rate overestimates the purchase price significantly as the service cycle increases. 5% is therefore considered a reasonable proximate.

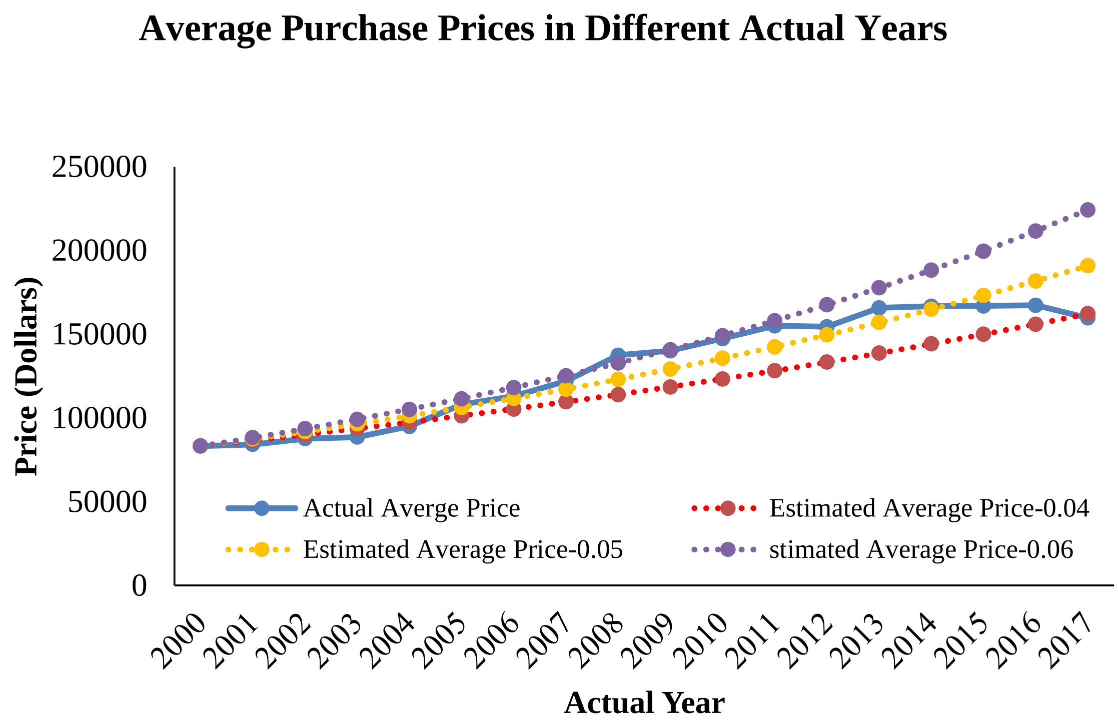


Figure 5 The average purchase values and estimated purchase values with different inflation rates.

In the following step, maintenance costs in different years are adjusted accordingly based on the records of their actual years. In this study, year 2017 is set as the base, and all maintenance costs recorded from the previous years are adjusted with the formulation below:

$$Maintenance_{adjusted} = Maintenance_i * (1 + 0.05)^{2017-i} \quad (10)$$

where $Maintenance_i$ represents the actual maintenance costs recorded at the i^{th} actual year. The aggregated maintenance costs in all service years (from 1 to 16 years), the average maintenance costs per truck per mile in different years, and the cumulative average maintenance costs are shown in Table 2.

Table 2 Detailed information regarding maintenance costs.

Service year	Number of trucks	Total cost with inflation	Total mileage	Average cost (per unit per mile)	Cumulative average Cost
1	451.00	2141821.75	4720914.00	0.45	0.45
2	457.00	2120095.47	4692610.00	0.45	0.91
3	465.00	2782768.09	4765585.00	0.58	1.49
4	480.00	3376872.04	4595855.00	0.73	2.22
5	462.00	3603744.39	4498135.00	0.80	3.03
6	462.00	4048765.37	4104520.00	0.99	4.01
7	471.00	4324249.44	4023063.00	1.07	5.09
8	476.00	4425360.46	3683168.00	1.20	6.29
9	436.00	4211407.75	3307228.00	1.27	7.56
10	436.00	4293625.37	3167493.00	1.36	8.92
11	416.00	4190546.59	2869841.00	1.46	10.38
12	405.00	4059009.48	2510458.00	1.62	11.99
13	388.00	3770801.03	2299985.00	1.64	13.63
14	379.00	3520676.26	1938350.00	1.82	15.45
15	365.00	2787833.64	1620040.00	1.72	17.17
16	304.00	2044549.29	1051591.00	1.94	19.11

5.2.2 Depreciation Cost and Surplus Value Curves

To obtain depreciation curve, the percentage of depreciation in Equation 2 needs to be determined first. In this study, we decided to use the average resale value at the 16th service year, which is \$8,109, as the surplus value *s*, and the years of useful life *n* is 16 correspondingly. This is because the 16th service year has the highest number of resale records as shown in Figure 1, which provides a larger sample size on the trucks' surplus value. Meanwhile, the average purchase price in 2017 (\$159,750) is used to indicate the actual purchase value *c* in Equation 2, since all maintenance costs are adjusted to the costs in 2017. As a result, the calculated percentage of depreciation *p* is 17%. Once *p* is calculated, the depreciation cost in each service year and the cumulative depreciation cost can be calculated. The snowplow trucks' cumulative depreciation costs and surplus value with the increase of service span are illustrated in Figure 6.

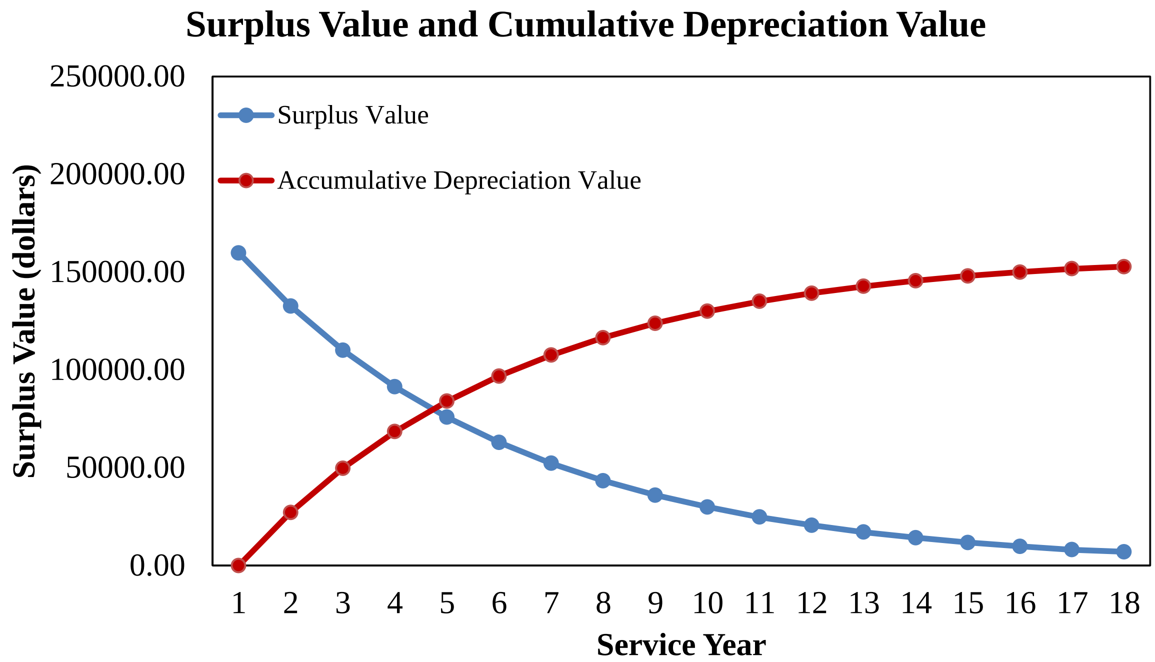


Figure 6 Accumulative depreciation costs and surplus value curves.

Figure 6 shows that the truck's surplus value continuously drops as service span increases. Since DB method follows an exponential decay in value, the decrease of surplus value in the first several years is very pronounced. At the 7^{th} service year, a snowplow truck merely remains one-third of its total value. Yet the surplus value steadily declines after that due to the entity's low remaining value. This indicates that if the snowplow truck fleet is replaced frequently, the total cost can be extremely high because of the initial expotential decay in surplus values. Hence, the optimal total cost should balance between depreciation cost and maintenance cost.

5.2.3 Total Cost Curve and Optimal Life Cycle

In the last two subsections, maintenance cost in different service years and cumulative depreciation cost are obtained. In this subsection, Equation 5 is implemented to calculate AATCs per truck per mile with different service spans. AATCs for life cycle from 1 year to 16 years are calculated and presented in Figure 7.

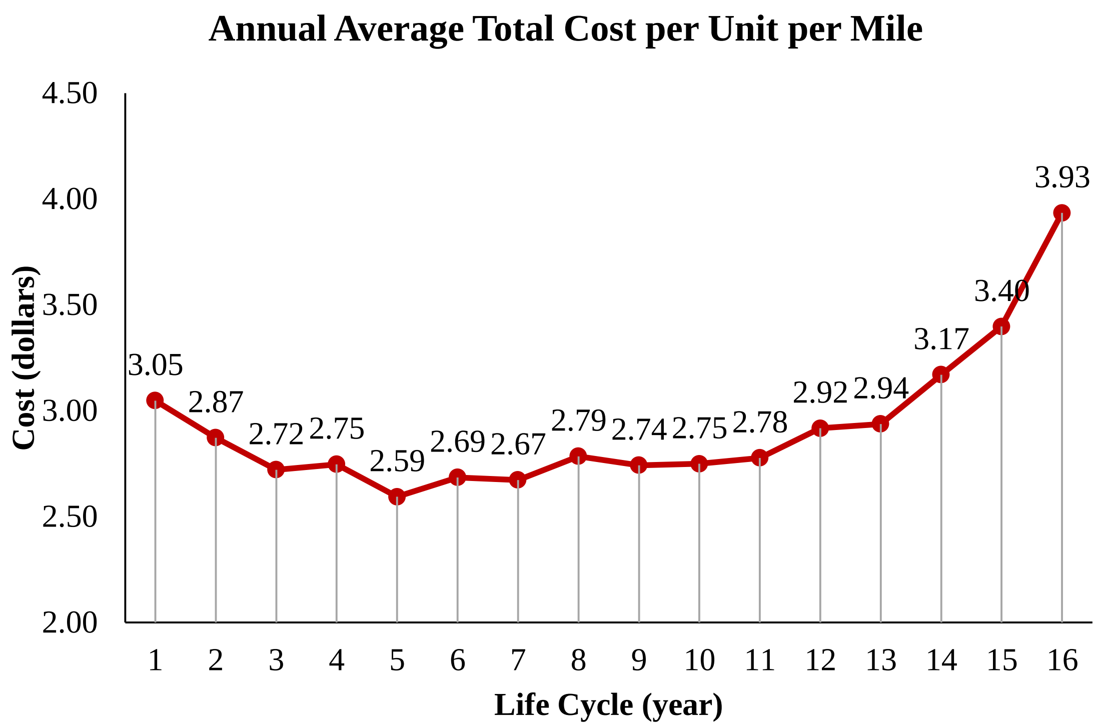


Figure 7 AATC per truck per mile with different life cycles.

Figure 7 indicates that the AATC drops first and then increases gradually with the increase of life cycle. For the initial service years, although annual depreciation cost is relatively high, maintenance cost is also marginal. This is due to the fact that assets usually maintain satisfactory performance as they first start the service. However, maintenance costs start to mount up with longer service years, which are caused by more frequent malfunctions and repairs. The optimal life cycle can be easily identified as 5 years, where the AATC is $2.59 per truck per mile. Yet the current service ages for Class 8 snowplow trucks are mostly concentrated between 15 to 19 years. Assume there are 500 snowplow trucks operating annually with average working mileage of 8,000 miles per truck. If the life cycle for all trucks has shortened from 15 (AATC is $3.40 per truck per mile) years to 5 years, UDOT can save approximately $3.24 million every year. The implementation of a recommended replacement strategy thus could result in significant cost savings.

In fact, the snowplow trucks are all assigned with specific working regions. Due to the terrain differences and miscellaneous other reasons, the optimal life cycles may vary across different geographical areas. As a result, we perform the cost-benefit analysis based on different regions in the State of Utah. The trucks' region classification information is extracted from the Verizon AVL trajectory database from January to March 2018. Note that the data does not include all the trucks used for the state-wide analysis, due to the relatively short period of time - only 471 snowplow trucks are recorded during those two months, yet 831 trucks' records are used for the state-wide analysis from years 2000 to 2017. However, the results can still provide much valuable information on how the performance might differentiate across regions. Figure 8 shows the number of snowplow trucks in each region, namely the Salt Lake City, Ogden, Orem and Richfield regions, and Figure 9 illustrates their corresponding activity distribution.

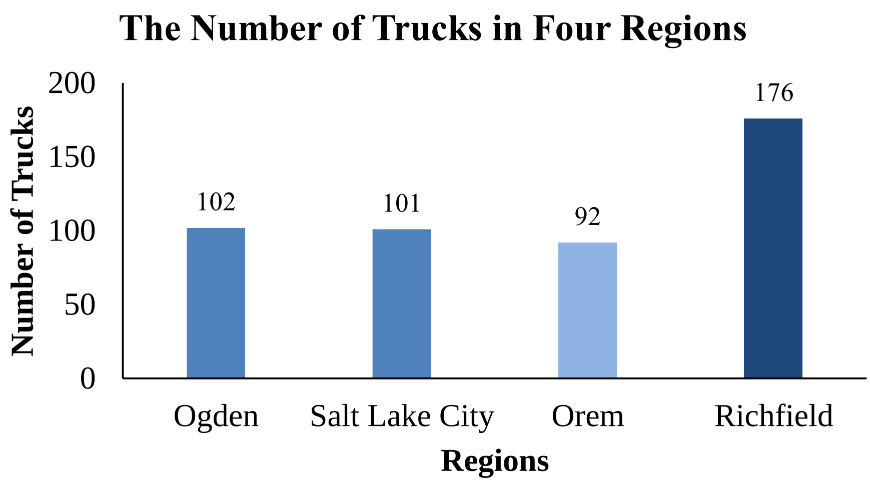


Figure 8 The number of snowplow trucks in four regions.

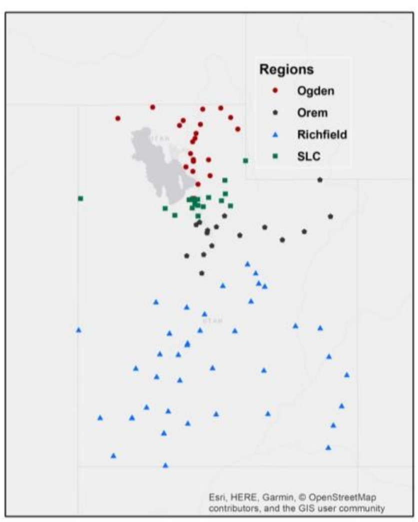


Figure 9 Distribution of snowplow trucks in four regions.

Figures 10 through 13 further delineate AATC values by the four different regions.

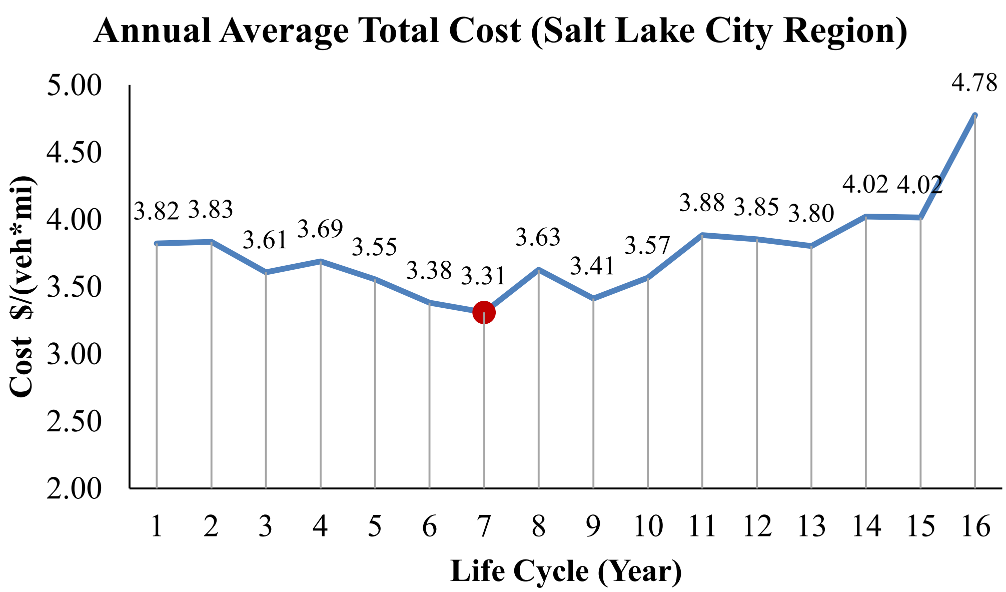


Figure 10 AATC per truck per mile in different replacement years (Salt Lake City Region).

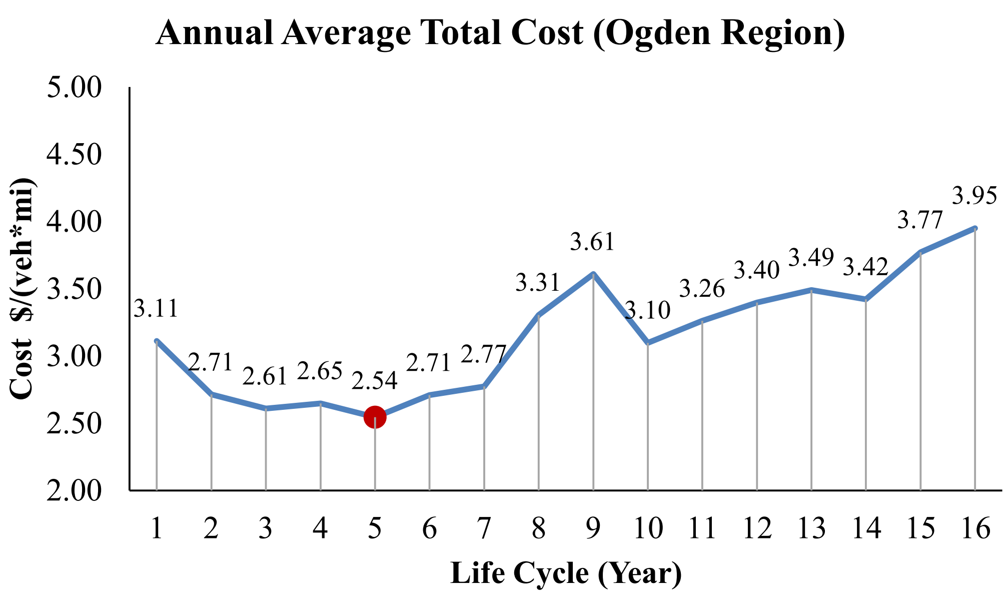


Figure 11 AATC per truck per mile in different replacement years (Ogden Region).

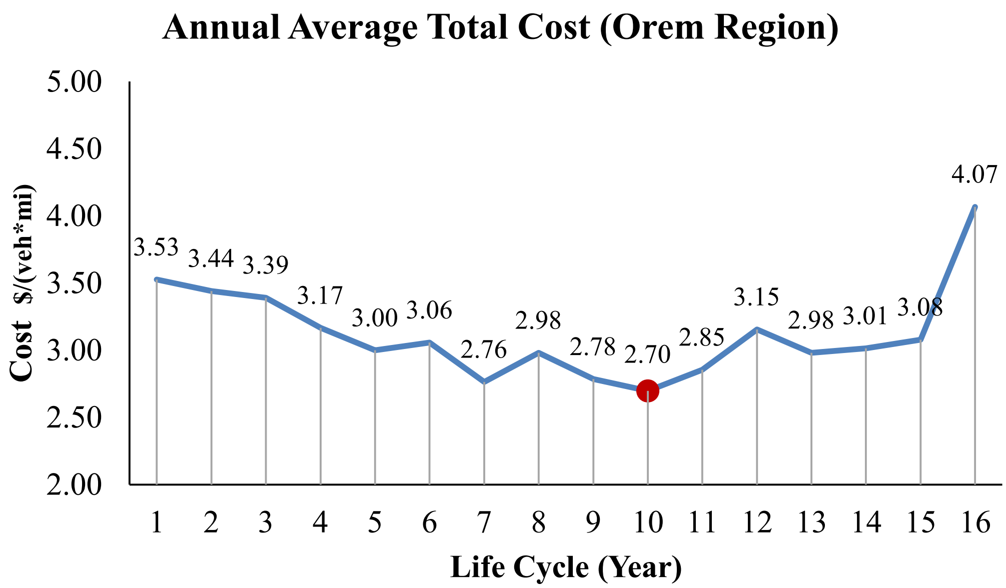


Figure 12 AATC per truck per mile in different replacement years (Orem Region).

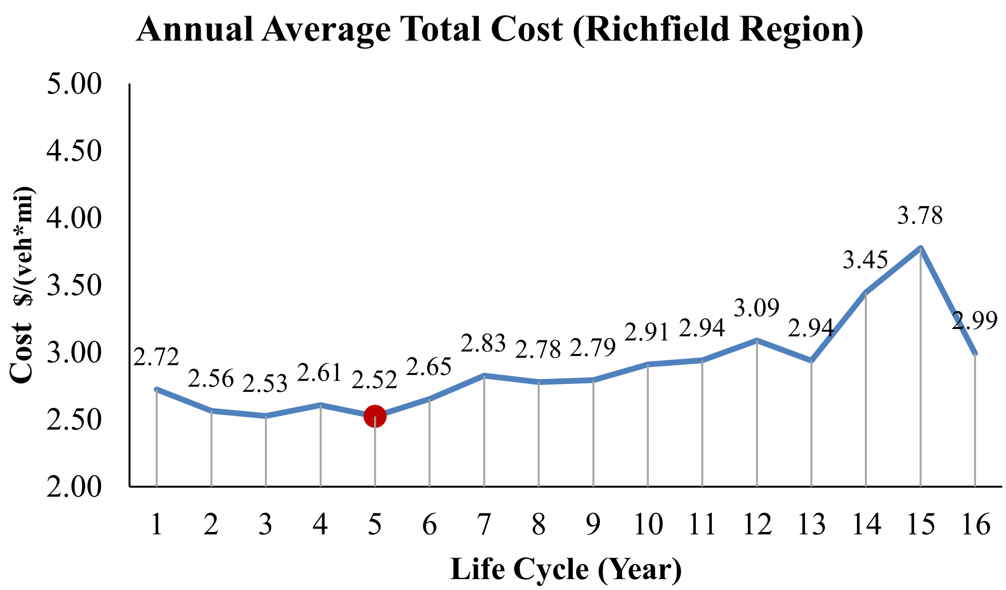


Figure 13 AATC per truck per mile in different replacement years (Richfield Region).

Figure 14 presents the previous results on the same horizon and Figure 15 illustrates the comparison using the state-wide value as a benchmark.

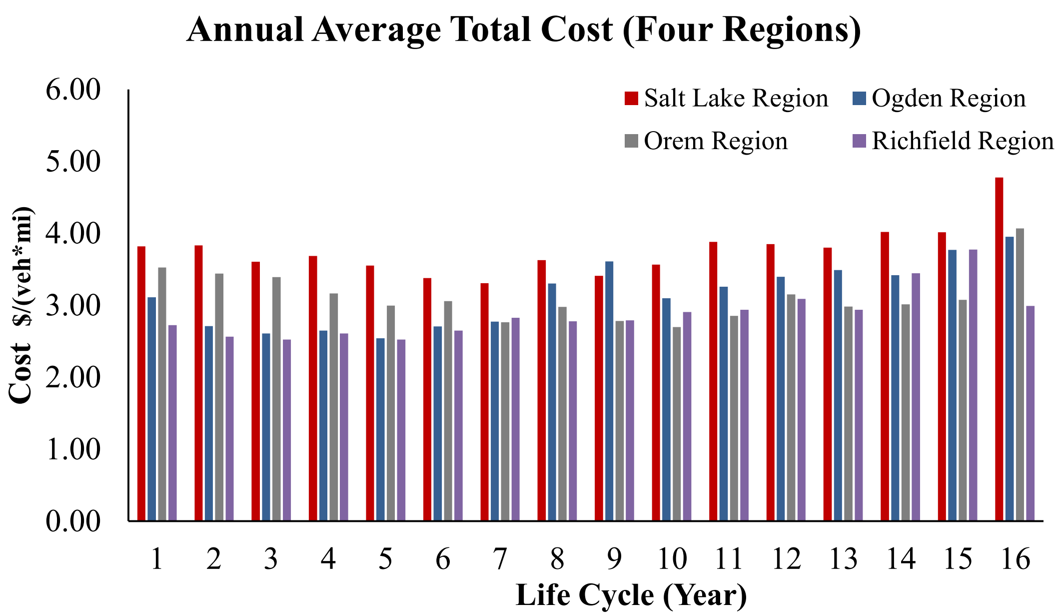


Figure 14 AATC per truck per mile in different replacement years (four regions).

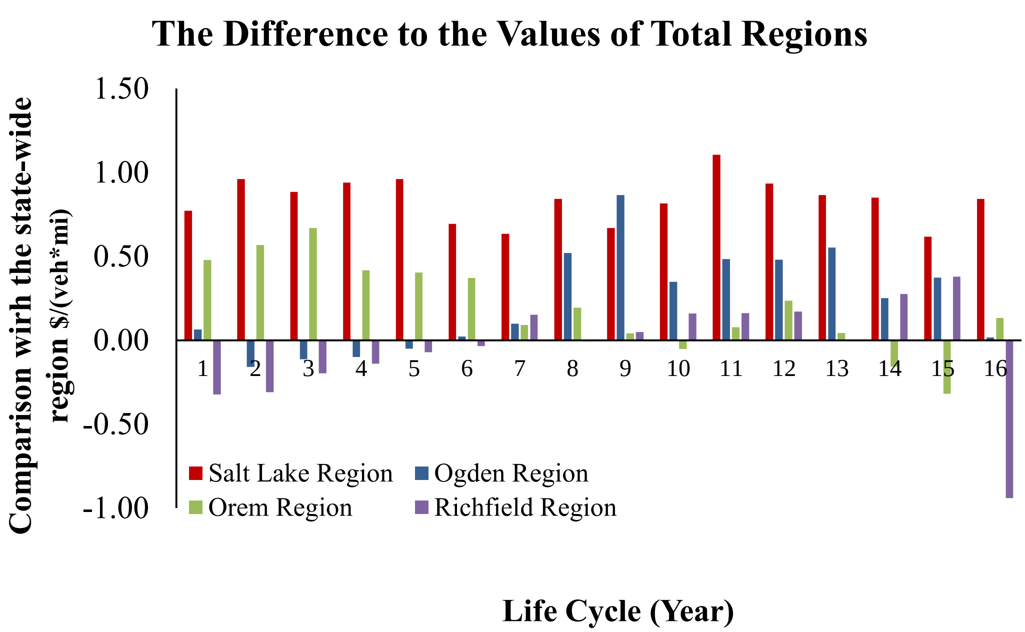


Figure 15 Cost comparison using state-wide value as a benchmark (four regions).

Based on the results presented above, there are several findings worth mentioning. First, the optimal replacement years for the State of Utah is determined as 5 years. However, when we split analysis into four regions, the results vary. The Ogden and Richfield regions are still consistent with the state-wide result (5-year as optimal replacement cycle). The Salt Lake City region has an optimal year at 7 and Orem is postponed to 10. This result indicates that the snowplow trucks which serve Salt Lake City or Orem regions can potentially have their lifetime service extended. Note in Figure 15 that trucks serving the Salt Lake City region have the highest cost across all service years, and the values surpass the state-wide average. This suggests that those trucks are relatively costly to maintain. On the contrary, trucks serving the Richfield region have a relatively lower cost.

5.3 Performance Prediction by RF Model

5.3.1 Data Post-Processing

Data post-processing involves data cleaning, normalization, transformation, feature extraction and selection, etc. It oftentimes has a significant impact on generalization performance of supervised ML algorithms (Kotsiantis et al., 2006). The following subsections present the data post-processing we conducted for RF.

In order to predict truck performance, all trucks are categorized into four groups based on the severity of their repairs. For the entire 388 snowplow truck fleet, the numbers of trucks in Ranks 1 to 4 are 264, 83, 34 and 4, separately. The imbalanced classes could result in the model downplaying features in the minority classes. To fix this issue, we use a resampling technique to sample the minor classes with replacement until the sample sizes are approximately equal across classes. Consequently, the final dataset includes information from 997 trucks. The number of trucks in Rank 1 remains the same, while the numbers of trucks in Ranks 2 through 4 are populated as 249, 244 and 240, separately.

5.3.2 Parameter Tuning and Performance Measurement

Standard practice of ML involves splitting the dataset into training set and test set, where training set is used to train the model and test set is used for evaluating performance of the model to the unknown dataset. Before training, some hyperparameters (e.g., the number of trees in RF) should be chosen manually to achieve better predictive performance. However, we run the risk of overfitting if the hyperparameters are directly tuned on test set because the information of the test set can “leak” into the model and consequently fails to report the generalization ability. To address this issue, another portion of the entire dataset, usually referred to as “validation set”, is held out to enable the evaluation of trained models and to choose the optimal hyperparameters. We then can apply the models with the best hyperparameters to test set to report on generalization performance. One potential drawback of this method is that it reduces the size of training data by partitioning the available data into three parts (i.e. training, validation and test sets). One remedy to this is to use the K-fold Cross-Validation (K-fold CV) (Kohavi, 1995). With K-fold CV approach, the data is still split into training set and test set. Yet we further partition the training set into K subsets with equal size. Each time, one subset is used as a validation set, and the remaining K-1 subsets are used to train the model. This process is repeated K times and the hyperparameters with the best average performance on validation set are chosen. Finally, we apply the selected hyperparameters to the test data. Empirically, K is set as 5 or 10 since it can lead to less bias and reduce the computational cost (Rodriguez et al., 2009). In this paper, we shuffle the data and split it into 80% as training data and 20% as test data, and K is set as 5.

Two performance measurements (i.e. classification-accuracy score and confusion matrix) are used for this multi-classification prediction. Generally, the multi-classification problem is solved by transforming it into a binary classification problem through one vs. one strategy. For a binary classification problem, all samples can be divided into two classes (one class is identified as positive class and the other one as negative class). One vs. one strategy assumes one class as positive class and other classes as negative. We will have N binary-classifiers, where N is the number of classes. In this study, N equals 4 as all samples are classified into four classes (Ranks 1 through 4). The classifier will output a list with each number in the list representing prediction probability to the index-based class. The final predicted class of the input is the class with the highest prediction probability. For example, when predicting the *i*th sample’s repair rank, if the prediction output is [0.3, 0.4, 0.8, 0.2] for Ranks 1 through 4, separately, the repair rank will be predicted as Rank 3. To measure the performance of the model, the classification accuracy score is used to indicate the models’ predicting ability, which is calculated as:

$$S = \sum_{k=1}^{K} \frac{N_{k\_correct}}{N_k} \tag{11}$$

where K is the number of classes, $N_{k\_correct}$ is the total number of samples correctly predicted as class k, and N_k is the total number of samples actually in class k. The classification accuracy score measures the correct predictions of the model compared to the total number of data points, and it is considered a good measurement for balanced multi-classification problem (Bukhsh et al., 2019).

Hyperparameters for each model are optimized to yield the lowest prediction error. For RF, the number of trees M is manually adjusted from 1 to 1000. The training and validation curves are presented in Figure 16. Hyperparameters with the highest average accuracy score on the validation set across the 5-fold CV is selected for the final models. The validation curve shows that when the number of trees M is above 50, the average classification-accuracy scores on validation set are higher than 0.9, and the classification ability does not improve much beyond 500. We therefore set M as 500 to avoid overfitting.

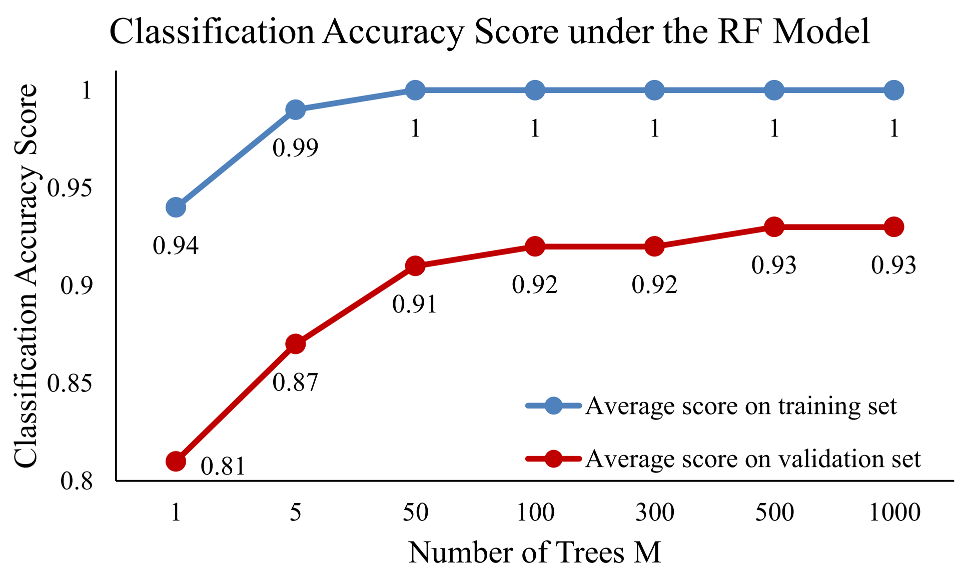


Figure 16 The average classification accuracy score under RF by performing 5-fold CV.

After parameters have been chosen for the model, final model is performed on the test set. The accuracy scores of RF on the test set is 0.92, which indicates a high prediction accuracy. To measure the performance of the classification model more explicitly, confusion matrix is used on the test dataset to illustrate the finer details of the results using different methods. Confusion matrix is often applied to allow easy identification of confusion between different classes. In the matrix, each row represents the instances in an actual class while each column represents the instances in a predicted class. The confusion matrix for this multiclassification problem is provided in Figure 17. As an example, the number in the first row and second column corresponds to the instances that actually belong to Rank 1 but are misclassified as Rank 2.

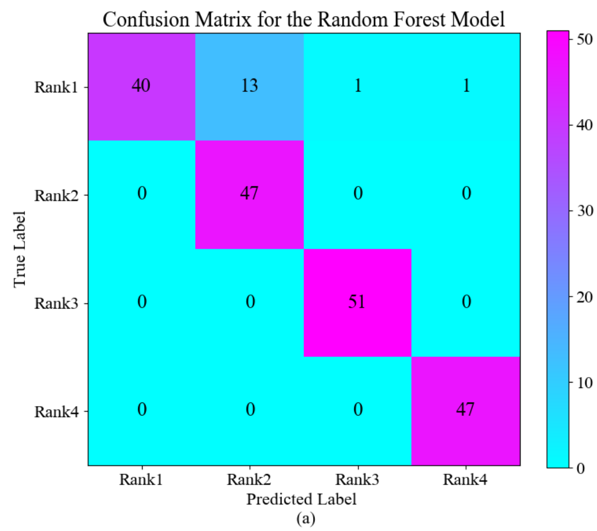


Figure 17 Confusion matrices for RF model on the test dataset.

In Figure 17, it is noted that most trucks are well classified except a small portion of trucks in Rank 1 being misclassified as Rank 2. Overall, it can be concluded that RF achieves good prediction performance of snowplow trucks based on the classification-accuracy score and confusion matrix.

5.3.3 Feature Importance Analysis

As mentioned earlier, one highlighted feature for RF is that it can interpret the importance of variables. Knowing the importance of features can help agencies better understand which features are dominant in affecting snowplow truck performance, and consequently prioritize strategies to address deterioration issues. Moreover, it can benefit model construction by filtering out insignificant variables and building a model with satisfactory prediction accuracy and less variables. Mean decrease impurity is implemented for each split in RF during the training process, and all features are ranked by the average decrease impurity across all trees. Table 3 presents the feature importance graph.

Table 3 The ranking of variables based on the importance to the performance of snowplow trucks, where the sum of importance coefficients equals 1.

Variable	Importance Coefficient	Variable	Importance Coefficient
Mi	0.33	Func	0.10
Fuel	0.16	Snow	0.09
Year	0.15	Area	0.03
Vol	0.13	Type	0.01

As shown in Table 3, working mileage appears to be the most important feature in affecting the performance of snowplow trucks, with its weight being twice as much as the second most important feature. Fuel consumption and service year are also main contributing factors that lead to performance deterioration. Besides, AADT, functional classification of roads that trucks serve, as well as annual average snow depth also matter to the performance. The results demonstrate that trucks working in different environments can have different performances even with the same work intensity. Also note that loading capacity and area types (rural vs. urban) have an insignificant effect to the major repair times. This means that if we drop these two variables from the dataset, the performance of the model may be only marginally affected.

In broad terms, endogenous features comprise 66% of the total factors and exogenous features account for 34%. In other words, current work intensity of a snowplow truck (e.g. working mileage and service year) should be treated as the top priority when replacement strategy is considered.

5.3.4 An Application of Performance Prediction

The proposed prediction model can be applied to estimate snowplow truck performance over the service time span. Such application can enable effective trend analysis regarding performance deterioration and correspondingly suggest a reasonable level of work intensity. For demonstration purposes, we choose AADT ranging from 0 to 60,000 veh/d to represent different working environments and working mileage in the range of 3,000 to 15,000 miles to represent different work intensities. For simplicity, we assume the class 8 snowplow truck's fuel consumption rate maintains steadily around 6 mpg during the entire operation (Hajibabai et al., 2014). Road functional classification and annual snow depth are set as 3.20 and 159.20 ml (average values across all trucks), separately. Lastly, service region is randomly chosen between urban and rural, and type of load is randomly chosen from types 104, 113 and 168, since these two variables only marginally impact the performance. Truck performances are predicted at the third, sixth, tenth and fifteenth years of service separately, and results are presented in Figure 18.

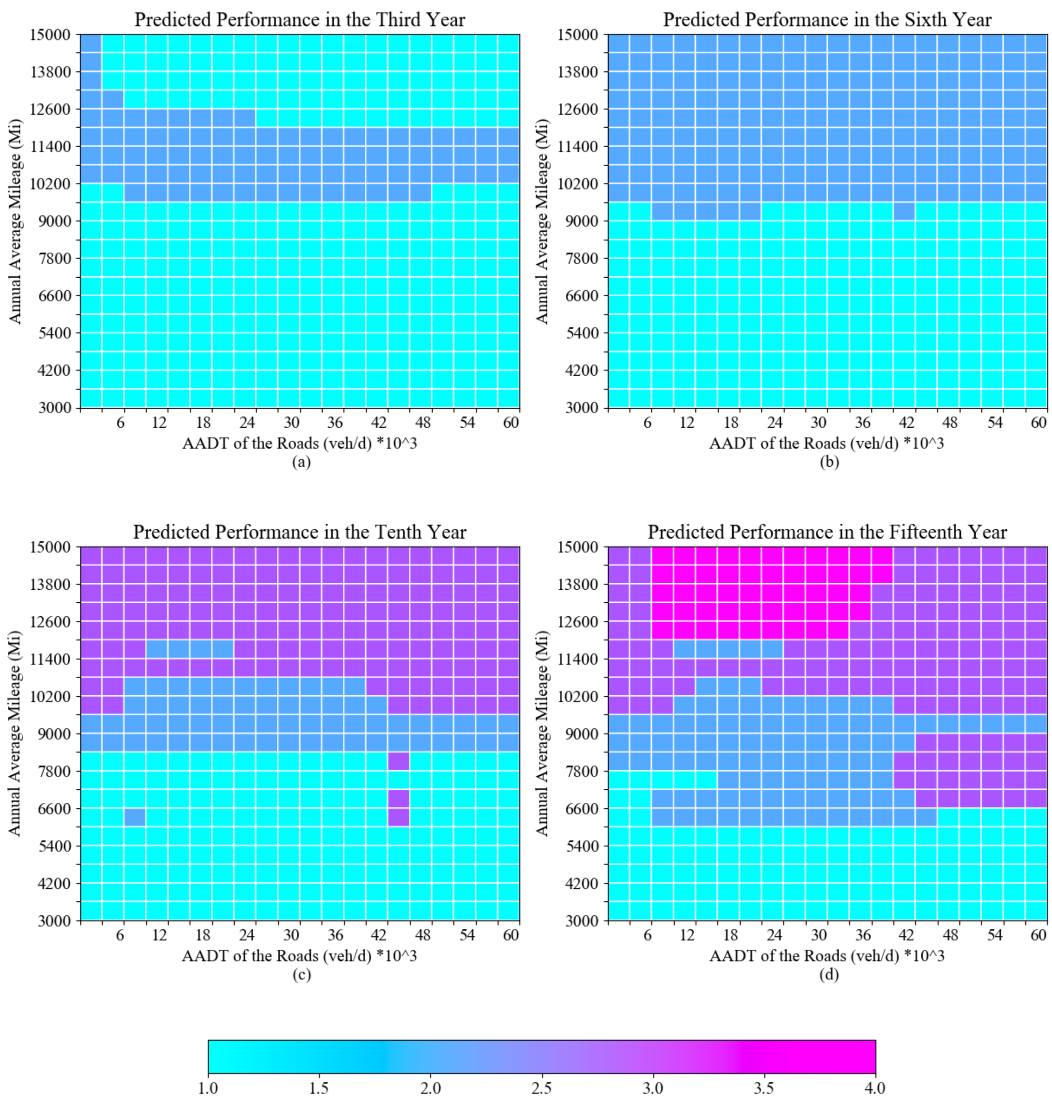


Figure 18 The change of major repair ranks of snowplow trucks across different work loads and working environments, where different colors represent different ranks.

As we can see in Figure 18, the change of ranks is more sensitive to the working mileage than AADT of roads that the truck serves at the same service year, which implies that working mileage is more dominant in affecting performance. We also notice that trucks working with high annual mileage (above 12,000 miles) are still in Rank 1 while trucks working with annual mileage between 10,000 to 12,000 miles are in Rank 2. This inaccuracy may be caused by the fact that training samples with high annual working mileage are scarce. Meanwhile, it can be noted that there is a trade-off between work intensity and performance, that is more working mileage leads to more frequent major repairs. In other words, the average working mileage could be appropriately controlled or allocated across trucks to prevent rapid performance deterioration. Specifically, trucks operating less than 6,000 miles annually maintain decent performance even after serving 15 years. Meanwhile, if we set the threshold at 8,000 miles, trucks can service continuously for 10 years while still keeping good performance, and if the annual working mileage is controlled below 10,000 miles, the truck can stay in good condition after serving over 6 years. This result can complement life cycle analysis by adjusting annual average working mileage in terms of the replacement year. In this way, it will lead to less repair cost and more utilization of trucks.

Variation among AADT is not as significant as among working mileage. However, if a snowplow truck serves roads with high AADT (over 40,000 veh/d), it should work less frequently than trucks serving other roads to avoid more repairs. For more accurate prediction, we need to take into account the variation of the functional classification of roads and annual snow depth as well, since they are also important factors for truck performance.

5.4 Summary

In this chapter, an in-depth analysis of the optimal life cycle and micro-level truck performance assessments are presented. To perform the cost-benefit analysis for obtaining life cycle with the minimal total costs, maintenance costs are adjusted by inflation rate and aggregated by corresponding service years, and then the cumulative depreciation costs curve is constructed by utilizing purchase and resale data. The result indicates that the statewide optimal life cycle is 5 years, and the optimal life cycle may vary across different regions. Moreover, RF is proposed to predict truck performance by utilizing operational performance features. This proposed model is capable of accurately predicting truck performance in different working environments and with different work intensities. Meanwhile, it identifies working mileage, fuel consumption, and service year as the top three most important factors leading to performance depreciation.

<u>6.0 CONCLUSIONS</u>

6.1 Summary

Snowplow trucks' performance can affect the road condition and traffic safety during the winter season, especially in regions where storms are frequent and unpredictable. Thus, the optimizing model is needed to ensure high efficiency and capability of snowplow trucks. This project focused on estimating the optimal life cycle and predicting the operational performance of Class 8 snowplow trucks managed by UDOT.

To achieve the first goal, the cost-benefit model is used to provide a thorough analysis in search of the optimal year for the replacement of the specific type of snowplow trucks. The available maintenance and operation data from 2000 to 2017 justify the effectiveness of the data-driven approach. The results suggest a shorter replacement cycle than what is currently implemented, and provide additional guidance on the procurement, maintenance, and prioritized selection of Class 8 snowplow trucks.

To predict truck performance subsequently, RF is trained by utilizing both endogenous and exogenous features regarding operational performance and evaluated on a total of 388 snowplow trucks. Statistical analysis shows a high prediction accuracy of RF on test dataset. Moreover, mean decrease impurity is implemented to explore which variables are significant in deteriorating performance of snowplow activities. The ranking of those features can provide a better understanding of what causes the lowering of performance and can help transportation agencies refine their trucks' replacement strategy effectively at the micro-level. In addition to feature importance analysis, we applied RF to visualize the change of truck performance with the increase of the service year by varying work intensity and working environments of those trucks. The results suggest a reasonable range of annual average working mileage based on replacement year for the purpose of preventing quick deterioration of their performance.

6.2 Findings

The findings in this project are summarized as follows:

6.2.1 Optimal Life Cycle for Class 8 Snowplow Trucks

The life-cycle analysis indicates that AATC curve decreases initially and then starts to mount up with the increase of service span. One of the key findings of this project is that the AATC reaches the lowest average costs when the replacement cycle is 5 years (for trucks of the entire state) with the annual average total costs being $2.59 per mile for each truck, assuming the inflation rate and the estimated depreciation cost are accurate. When performing the cost-benefit analysis by different regions, the results from the Richfield and Ogden regions remain the same, whereas trucks serving the Salt Lake City and Orem regions tend to have longer life cycles (7 years and 10 years, separately) than the statewide optimal life cycle. Currently, most snowplow trucks managed by UDOT function for over 13 years. This result suggests accelerating the replacement cycle in order to avoid higher accumulative maintenance costs.

6.2.2 Truck Performance Prediction with RF Model

By utilizing the exogenous and endogenous features regarding operational performance of snowplow trucks, RF is capable of predicting truck performance with high prediction accuracy. The importance of those features to performance is further analyzed by the mean decrease impurity method. The results show that working mileage, fuel consumption, and service span are considered as the most important features influencing truck performance. In broad terms, endogenous features comprise 66% of the total factors, and exogenous features account for 34%. Compared with exogenous features, endogenous features predominantly affect truck performance statewide. We therefore propose to set a threshold limit on work intensity for trucks working in different environments to maintain them in good condition and prevent further repairs.

6.3 Recommendations

According to the study developed in this research, the suggested optimal life cycle for Class 8 snowplow trucks managed by UDOT is 5 years on the statewide level. For trucks serving at some regions (i.e. the Salt Lake City and Orem regions), they tend to have longer service spans. However, most Class 8 snowplow trucks were disposed over 13 years of utilization. This longer service span can incur more frequent major repairs and higher maintenance costs. As a result, UDOT should shorten the average life cycle for Class 8 snowplow trucks to cut down overall expenses.

In fact, a small portion of snowplow trucks can still function with satisfactory operational efficiency over the calculated optimal life cycle. The proposed RF can help UDOT accurately identify the performance of snowplow trucks with a variety of conditions, which can complement the replacement strategy effectively. Moreover, the results indicate that both exogenous and endogenous features regarding snowplow operations can significantly impact truck performance. Hence, we recommend that trucks serving roads with high-traffic volumes should function less than trucks serving regular roads to reduce the speed of performance deterioration.

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